Estimating Fire Use Workload and Workload Fulfillment

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This paper documents our progress in developing Wildland Fire Use (WFU) workload scores and in developing resource workload fulfillment scores. We have completed the workload estimation process for fires and resources. This analysis was enabled by convening a panel of WFU experts who provided data from 202 WFU fire records in consultation with Howard Roose.

INCLUDING WFU IN FPA-PM

Fire policy and fire management are evolving to better recognize a spectrum of initial response including initial attack (IA) and WFU. WFU is increasingly used across the federal wildland fire management agencies, making WFU an important extension of the Fire Program Analysis System. Consequently, the FPA economic model is being assessed for expansion to include WFU events for inclusion into the integer program. Because there is no record of analytical work performed on WFU, new analysis is required to integrate WFU with IA.

Rideout and Kirsch (2002) discussed how WFU can be included in an optimization process that integrates WFU with IA. Including WFU was accomplished by expanding the objective function to include both “weighted acres protected” from IA and “weighted acres improved”(WAI) resulting from use of wildland fire. Weighted acres improved are obtained when a WFU fire event has been accepted by the economic model. For the accepted WFU, acreage would be multiplied by its weight to calculate WAI. To relate the objective of WAI to cost and to the resources used, Rideout and Kirsch suggested generating a WFU workload and fire resource workload fulfillment scores that would parallel the approach used in initial attack. A parallel approach would also foster consistency between IA and WFU as the initial response (IR)

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1 This paper or updates can be attained at the lab website: http://taurus.cnr.colostate.edu/projects/fel/

construct is developed. The duration of resource deployment was used as a decision variable in the prototype integer program modified for WFU. Background on the IA workload approach is provided in the next paragraph to establish a context for WFU workload analysis.

Initial attack workload is commonly defined by fire containment where the fire's perimeter is compared with fireline produced by firefighting resources. The fire generates workload by growing its perimeter. While it is recognized that wildfire workload is much more complex, the fire perimeter has been used as a generally acceptable workload proxy. Firefighting resources are deployed to fulfill the workload by producing chains of fire line. Some fire resources such as hand crews directly produce fire line and other fire resources, such as water tenders, indirectly produce chains of fire line in the model. Each firefighting resource is assigned a workload fulfillment score in chains of fireline production per hour. Although unrealistic, it is customary to assume that IA fireline production is linear across fire resources for the purpose of modeling IA. When the length of fireline constructed by all of fire fighting resources exceeds the fire's perimeter, the fire is "contained" and thus, the fire's workload is fulfilled. Fire resource workload fulfillment is recognized to be more complex than this, but linear applications of line production have provided an accepted proxy for workload fulfillment for some time.

The comparison of fire workload to fire resource fulfillment scores provides an important parallel to our WFU problem, but there are also important distinctions. Perhaps the most important distinction is arrived at by recognizing that WFU fires are managed in various ways to benefit the landscape such that articulation of a single physical proxy, such as perimeter, to define the overall workload is unavailable. For example, a WFU event may require various combinations of perimeter and point protection occurring at various times and in various combinations during the fire event. While the desired outcome of the WFU event can be defined, the daily relationship between fire resources and the physical condition of the WFU event is complex and unknown. Another important distinction is that WFU events can have substantial variation in duration and size. For example some WFU events last a few days while others might last for most of the season. A WFU event could burn a few acres or burn a significant portion of the landscape. Therefore, our approach to workload estimation uses data records on the three key physical attributes (size, duration and complexity) at their termination to predict WFU workload and presumes that the optimizer addresses duration.

In WFU events, the optimizer would select the most efficient combination of resources required to fulfill the fire use workload. Workload and fire resource workload fulfillment can be summarized as:

Each WFU event would have a defined workload predicted based upon its size, duration and complexity

Each WFU fire resource would have a daily workload fulfillment score and a daily cost.

EXPERT OPINION AND WFU DATA

Because no suitable data were available on WFU events, Howard Roose convened a panel of WFU experts to supply WFU data, expert opinion, and data interpretations central to estimating the workload for WFU events. The experts were selected for their knowledge, experience, broad representation of federal agencies, and geographic regions. Our panel met at the Fire Economics & Management Laboratory at the College of Natural Resources at Colorado State University on

June 22-24, 2004. Experts included: Howard Roose, Len Dems, Bill Clark, Brad McBratney, Fred Wetzel, Patti Koppenol, and Marsha Henderson. The panel provided data from agency records for 202 fires from the following regions: Alaska (AK), Southern (SE), Northern Rockies (NR), Great Basin (GB), Rocky Mountain (RM), Southwest (SW), and California (CA).

Because estimates of WFU workloads had not previously been made, the experts discussed and agreed upon how to make such assessments. The experts discussed the conceptual model, its role in FPA, WFU, and how to arrive at management and monitoring scores in a consistent and meaningful way. The panel agreed to provide an expert management and monitoring workload score for each fire on a scale of one to nine where scores of one to three would be interpreted as low workload, four to six as "medium" workload and seven through nine as "high" workload. Individual fires were then discussed and assessed by the panel and assigned consensus management and monitoring workload scores. This required extensive knowledge of the WFU events and of the principle factors that contributed to its workload. The group also agreed that complexity could be modeled categorically as "High," "Medium" or "Low" for workload purposes. The group agreed to use the "Wildland and Prescribed Fire Complexity Rating Worksheet" as found in the Wildland and Prescribed Fire Policy Implementation Procedures Reference Guide. The data from the fire records included observations on fire size, duration, complexity and the set of fire resources used on each WFU event. Panel members also reviewed each record for completeness and accuracy. Data on the 202 WFU events are summarized in the Appendix of Charts.

Econometric Model for Estimating WFU Workload

We estimated WFU management and monitoring workloads as a function of fire size, duration and complexity:

Mgt. Workload = f(size, duration, complexity)
Mtr. Workload = f(size, duration, complexity).

By estimating models that predict workload as a function of size, duration and complexity from a given data set, we would provide the means of predicting the workload for a new observation. When a new WFU event is to be assessed, its predicted workload can be calculated by knowing its size, duration and complexity.

We assessed alternative approaches for modeling these functions and selected a technique known as the "binary regression tree" (RT) because analysis of the data revealed important non-linear behavior. The (RT) technique is an accepted method for modeling data characterized by non-linear interdependencies (Breiman et al., 1984). Binary regression trees are nonparametric and nonlinear in that no implicit assumptions are made regarding the underlying relationship between predictor variables and the dependent variables (i.e. the relationship is linear, or follows some specific non-linear like function (e.g. binomial, Poisson, etc.) or that they could be monotonic[2].

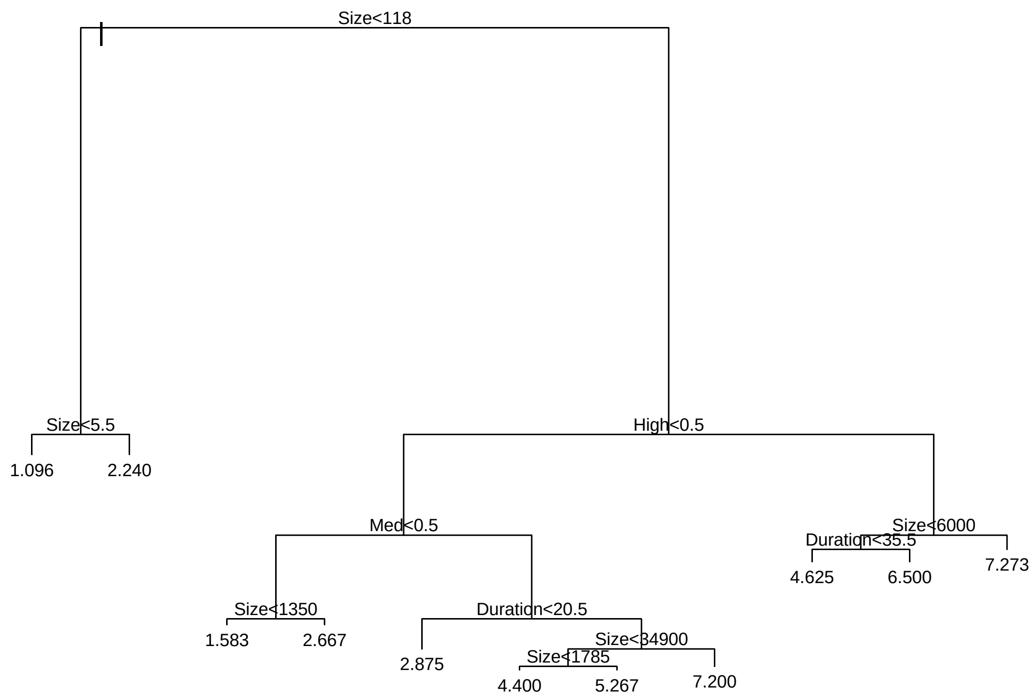
[2] A binary regression tree is a non-parametric approach to regression that compares all possible splits among the independent (continuous) variables using a binary partitioning algorithm that maximizes the dissimilarities among groups. Once the algorithm partitions the data into new subsets, new relationships are developed, assessed, and split into new subsets. The algorithm recursively splits the data in each subset until either the subset is homogeneous or the subset contains too few observations (e.g., < 5) to be split further.

An important advantage of the RT approach is that they are simple to use, adaptable, and make for rapid classification of new observations. They provide a straightforward way to explain why observations are classified or predicted in a particular manner. The predictor variables modeled in our RT application are fire size, duration and if the fire was of high or medium complexity (low complexity fires are implicitly modeled by the trees)[3].

Estimation of Management Scores

The overall fit of the model (tree) is represented by the R^2 value. The R^2 value for the management score RT is 85 percent meaning that bout 85 percent of the variation in scores can be explained by size, duration, and complexity. This tree shows that fire size is the most important factor in determining management scores. The amount of variation explained is proportionate to the vertical length of the branches in the tree. The vertical length for fire size is large relative to other branches indicating that size explains much of the variation in the model. For fires smaller than 118 acres, duration and complexity are not factors that affect the management score. For fires larger than 118 acres, complexity is the second most important variable and duration is also an important variable.

[3] To avoid over-fitting the management and monitoring models, we used a 10-fold cross-validation procedure (Efron and Tibshirani 1993) to identify the tree size that would minimize the total deviance. This procedure finds the optimal tree size for minimizing prediction errors. We evaluated the results obtained from this procedure and further pruned the trees to avoid over fitting.

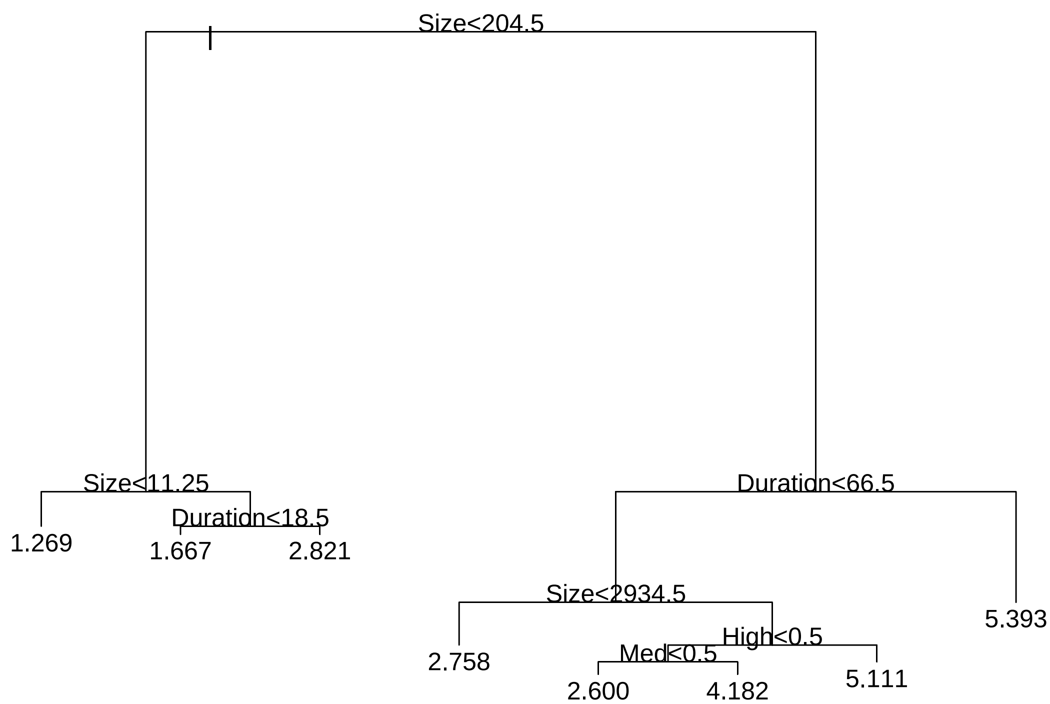


The numerical value at the end of each tree "node" is the predicted management score. This predicted score represents the total workload for the fire. An example will illustrate the use and meaning of the tree. Suppose a fire that was 1200 acres in size, lasted 43 days, and was of medium complexity.

1. Starting at the top of the tree we move to the right-hand branch because the fire was larger than 118 acres (if less than 118 acres move to the left-hand branch).
2. Next, if the fire was of high complexity. It is not so we move left.
3. If the fire was of medium complexity (again No goes to the left, Yes goes to the right).
4. Now we look at the fire's duration. Because the fire was 43 days long, we move to the right.
5. Because the tree requires additional size information, we move to the left and left again to arrive at a management score of 4.4!

This visualization of the RT process for arriving at a management score is useful for developing an understanding of the process. However, the sequence of sorting through the tree is effectively a set of "if-then" statements that can be programmed. We have programmed such a series in a companion spreadsheet where the user can insert the fire complexity, size and duration. With this information, the spreadsheet calculates the workload score.

Estimation of Monitoring Scores
We used the same approach for developing the prediction for monitoring scores. In monitoring, the estimated R^2 value is 0.62 meaning that about 62 percent of the variation in monitoring scores can be explained by using the RT approach when size, duration, and complexity are known. This tree shows that size was the most important factor (longest vertical limb) in estimating monitoring scores. For large fires (>204.5 acres) duration is the next most important consideration. The highest predicted monitoring score is an average of 5.4. The reason that there are not higher values predicted by the tree is that the number of observations with high monitoring values contained high variation relative to a small sample size. The chart "Number of Fires by Monitoring Score" in the Appendix of Charts shows how few observations were available with monitoring scores higher than six. With additional data on large WFU events, it might be possible to further develop the scoring process. The numerical value at the end of each tree "node" is the estimated monitoring score. This represents the total workload of the fire.



Another example illustrates the approach. Suppose our fire has 10,000 acres, was 100 days long, and was of high complexity. We first branch to the right because the fire was larger than 204.5 acres. At duration we branch right again because our fire was longer than 66.6 days. We arrive at a monitoring score of 5.4 recognizing that complexity was not used in this calculation because it was not useful in explaining differences in scores for fires that were large and lengthy. Note however, that complexity is useful in predicting scores for large fires that are not so lengthy. This is an example of a non-linearity in the data that is reflected in the RT approach. Any new fire can be applied to the regression trees to predict management or monitoring scores as long as its size, duration and complexity are known. We facilitated this process by developing a companion spreadsheet that is available on the Fire Economics & Management web site.

Fire Resource Fulfillment

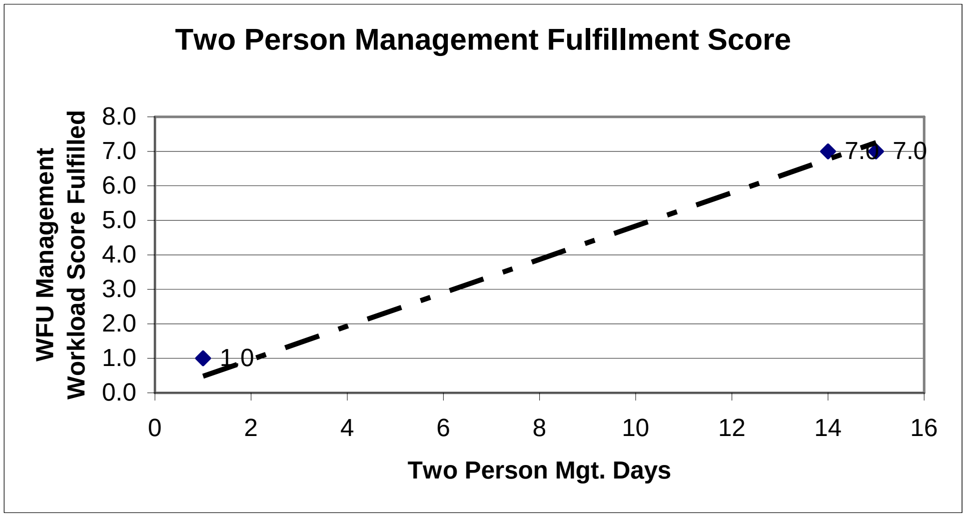
Fire resource fulfillment scores are needed to reflect the ability of each resource to fulfill the WFU workload. We estimated fire resource workload fulfillment scores by regresssing the fire workload against the number of days each resource was deployed to the fire. We only used records where a single resource was deployed to the fire and we used separate linear regressions to estimate the coefficient value for each resource. The regression coefficients estimate the daily contribution that each fire resource would make to fulfillment of the fire workload. Because there are many fire resources relative to the number of fires and few records where a single resource was deployed, we were unable to arrive at a complete list of estimated coefficient values. Our estimates, using a zero intercept model, are reported in Table 1.

WFU Workload Fulfillment Coefficients					
Row	**Fire Resource**	**Monitoring**		**Management**	
		Coefficient	No. Obs.	Coefficient	No. Obs.
1	7 Person Crew	2.50	2	NA	
2	5 Person Crew	NA		0.50	3
3	2 Person Crew	NA		0.48	3
4	Rotor Wing (RW3)	NA		0.76	5
5	Fixed Wing	0.28[4]	58	0.09	6
6	Engine 6 (E6)	NA		1.00	3

Table 1. Estimated fire resource workload fulfillment scores.

Interpretation of the coefficients is in **workload fulfillment per day** (equivalent) **of fire resource** application. For example, application of one day equivalent of a two person crew provided 0.48 towards fulfilling wildland fire use management score. The figure below illustrates the regression process by using the data for the two person crew in fulfilling the WFU management score. The coefficient defines the slope of the line in the figure.

[4] Despite the large number of observations, the fit for this regression was not very good.



Analysis of the resource fulfillment data indicated that providing credible estimates of fire resource fulfillment scores is problematic and complex because of the many interactions among the resources and because quality data are scarce. For example, the deployment of a resource pair (such as a crew with a rotor wing) is likely to provide different productivity than individual (separate) estimates. This suggests that such data on fire resource productivity is non-linear and that interactions may be important considerations in arriving at resource fulfillment coefficients. Further, when a group of resources are deployed, the group productivity likely depends upon both the mix of resources and the proportion of resource usage in the mix. For example, five days of a two person crew combined with one day of a helicopter likely has different productivity than one day of a two person crew combined with five days of helicopter deployment. And this productivity likely differs from the two person crew and the helicopter deployed separately. These estimates might also vary depending upon terrain and fuel conditions as they do in initial attack. These considerations also would apply to initial attack fire workload estimates.

APPLICATION TO THE INTEGER PROGRAM

The WFU fire and resource workload estimates are applied in the context of the integer program. The integer program selects qualifying WFU events based upon their contribution to effectiveness and their cost of management. Management cost depends upon the fire workload which depends upon the fire duration. Therefore, the way that duration is modeled has important implications for WFU events and for managing the tradeoff between IA and WFU.

Full Duration Deployment Assumption and its Implications

In the current optimization formulation, resources are either deployed or not deployed to fire events (IA and WFU), making the deployment decision binary. It is important to recognize that the interpretation of the decision variables currently assumes that if a resource is deployed to a fire event, it is deployed for the entire duration of the event. For example, on a 100 day WFU event a Type III Helicopter providing monitoring fulfillment would be deployed for the full 100 days, eight hours per day, totaling 800 hours of flight time and associated costs. This introduces potentially large errors for lengthy WFU events. These errors are related to the number and kind of resources deployed, the estimation of resource cost, and in the calculation of workload fulfillment. The assumption also introduces potentially large errors in evaluating the tradeoff between initial attack and WFU projects.

The assumption of full duration deployment means that it is impossible to directly apply the WFU workload and resource fulfillment scores developed in this paper. This occurs because the WFU resources (as estimated here) have daily equivalent workload fulfillment and daily equivalent cost, while the assumption precludes daily resolution. An alternative approach that treats the duration of deployment as a decision variable has the potential to remedy these problems. Andy Kirsch suggested the following application of the workload and workload scores. Note that his suggestion seeks to manage the error within the framework of the full duration deployment assumption and it is not intended to remedy the problem.

Suggestion

To manage the error we can change the duration implied by the binary decision variables from the full duration to one day. That is, deploy the resource for one day (one daily equivalent over the duration of the fire) or do not deploy the resource. The deployed resource would generate one day of workload fulfillment and one day of cost. If the fire workload is not fulfilled, then additional deployment would be required.

CONCLUSION

Including WFU into the overall initial response framework for FPA currently requires using estimates of fire and fire resource workload. This paper represents the first effort at arriving at such estimates. We found that estimates for both WFU and fire resource fulfillment scores were non-linear such that special considerations were required. In WFU, we applied the binary regression tree approach designed for addressing such non-linear relationships and our application appears to be sound. In fire resource workload fulfillment scores we only estimated resource fulfillment for the deployment of single resources. Providing a credible fire resource fulfillment score for each relevant resource would require a systematic process for gathering WFU workload data. At a minimum, several hundred more observations would be needed across a range of fire resource and fire resource combinations to provide the data necessary for a full listing of fire resource scores. The process might also consider that data gathered on past events reflects previous knowledge and technology regarding WFU events. Also, literature (that we have found) on initial attack workload estimations has not directly addressed the problem of interactions between the fire resources. A parallel data gathering process between initial attack and WFU events should also be considered. Finally, the restrictive assumption of full duration deployment introduces large error in the context of WFU and it should be reevaluated.

Literature Cited

Breiman L., Friedman J.H., Olshen RH, Stone IJ (1984). *Classification and regression trees*. (Wadsworth: Belmont, CA) 368pp.

Efron, B. and R.J. Tibshirani. 1993. *An introduction to the bootstrap.* (Chapman and Hall: New York, New York).

Rideout, Douglas B. and A. G. Kirsch. 2003. *Defining Initial Response: integrating fire use with Initial Attack*. Working paper V3.6 (September 9, 2003) Fire Economics and Management Laboratory, Colorado State University, Fort Collins, CO 14pp.

APPENDIX OF CHARTS

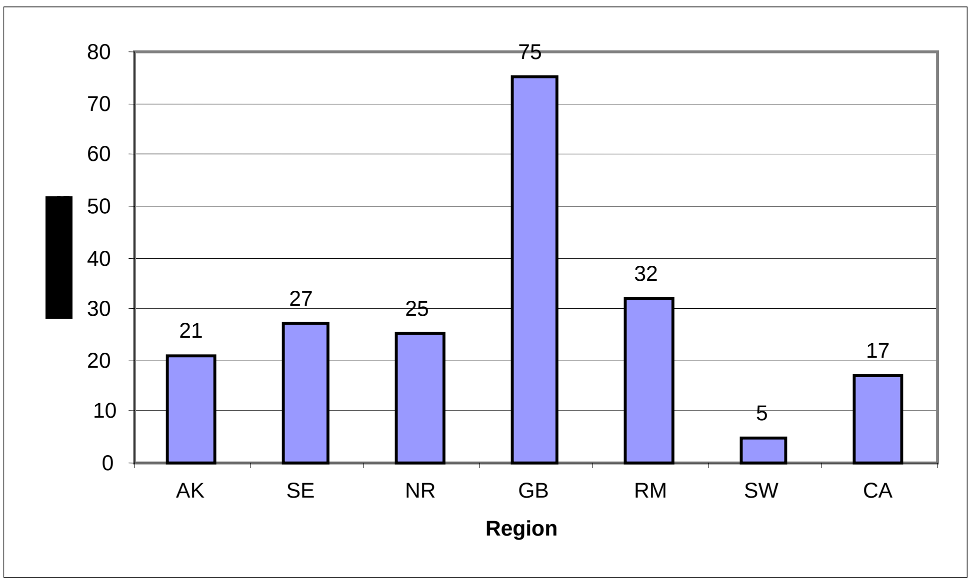
Data Summary

This is data that has never before been gathered and provides potentially important insight into the cost and productivity of use fires and their management. The following is a summary of the data obtained. First, the data set is summarized by fire attribute and then by fire resource. Next, data are summarized by region.

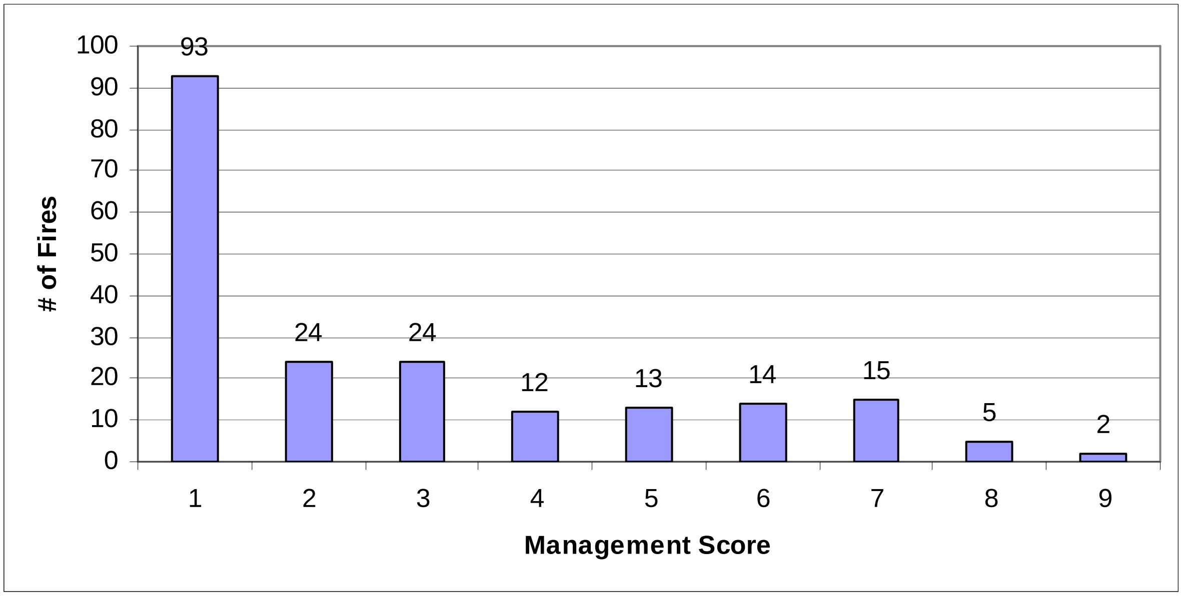
<u>Complete Data Set</u>

The complete data set includes a total of 202 fires. The following bar charts show the number of fires: a) within each region, b) within each management score, c) within each monitoring score, d) within each level of complexity, e) in each size class, and f) in each duration class. Also included is a graph (g) of the number of acres of fire from each region.

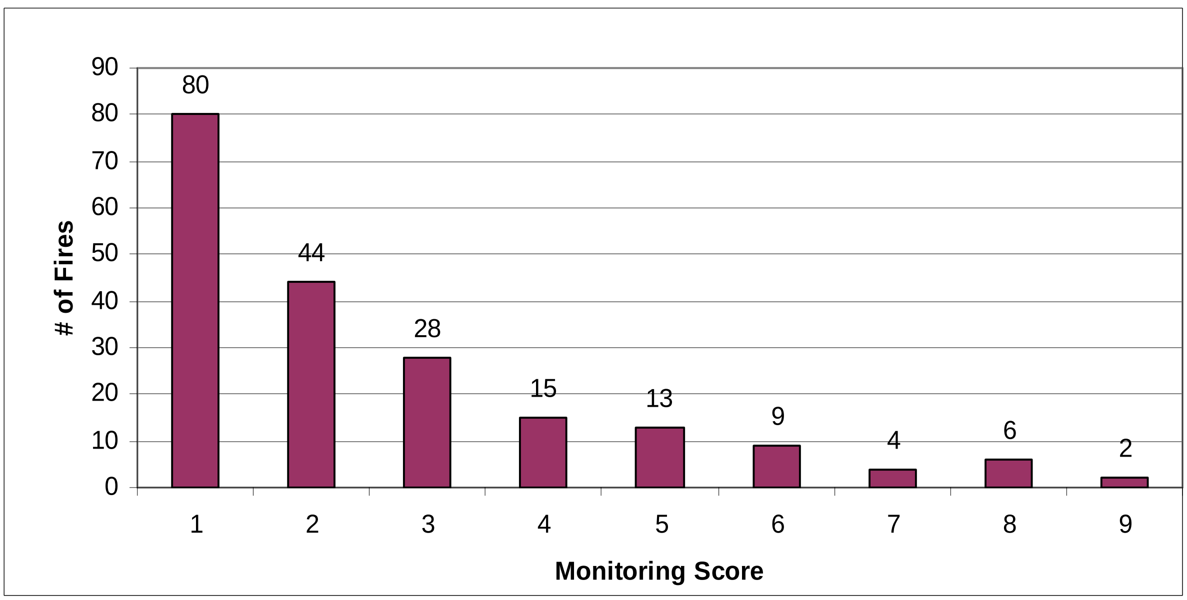
A: Number of fires by region.



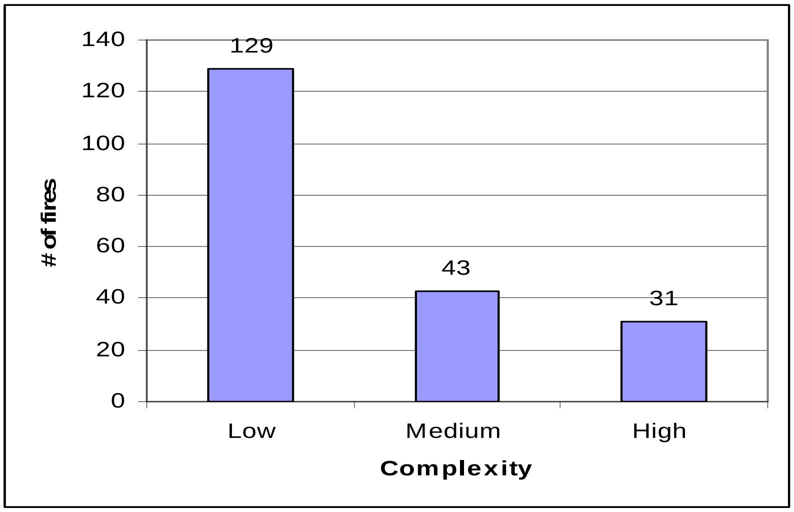
B: Number of fires by management score.



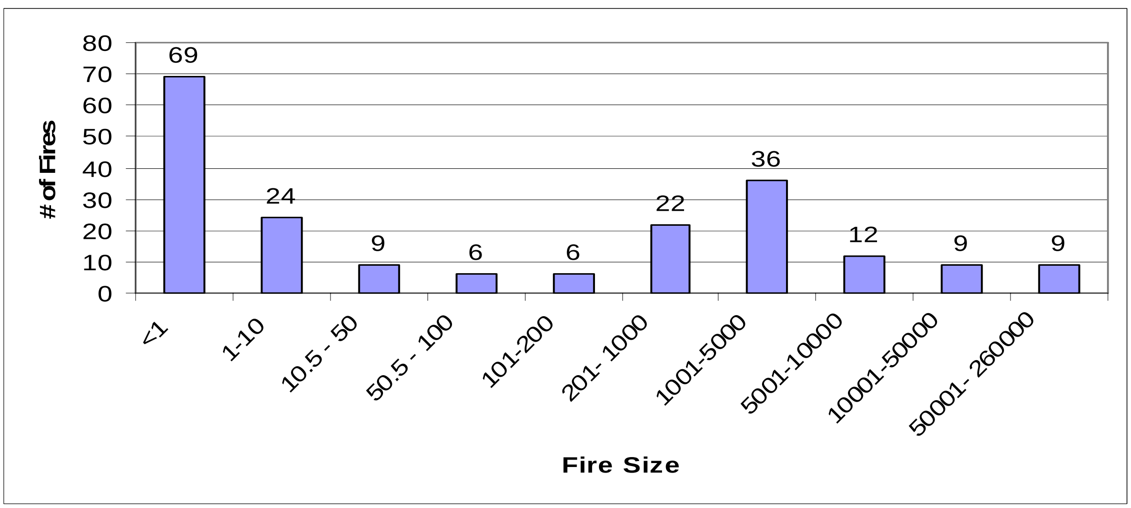
C: Number of fires by monitoring score.



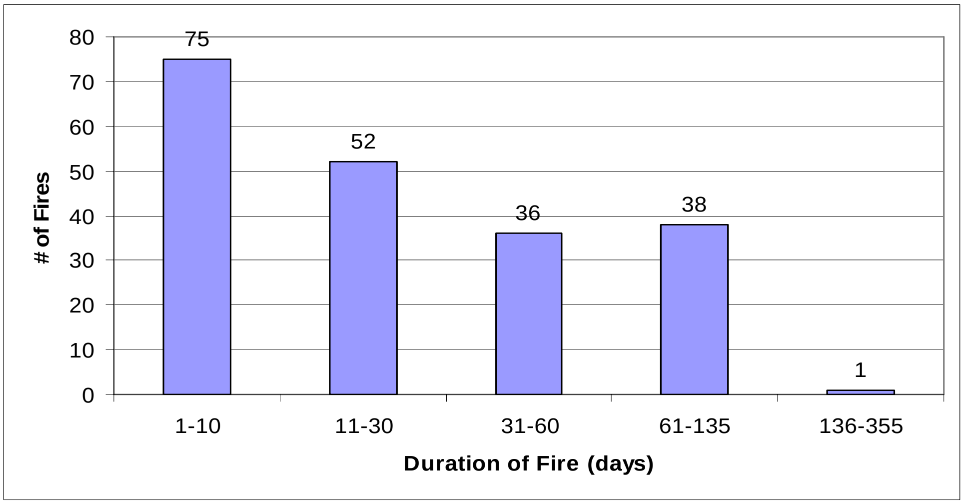
D: Number of fires by complexity score.



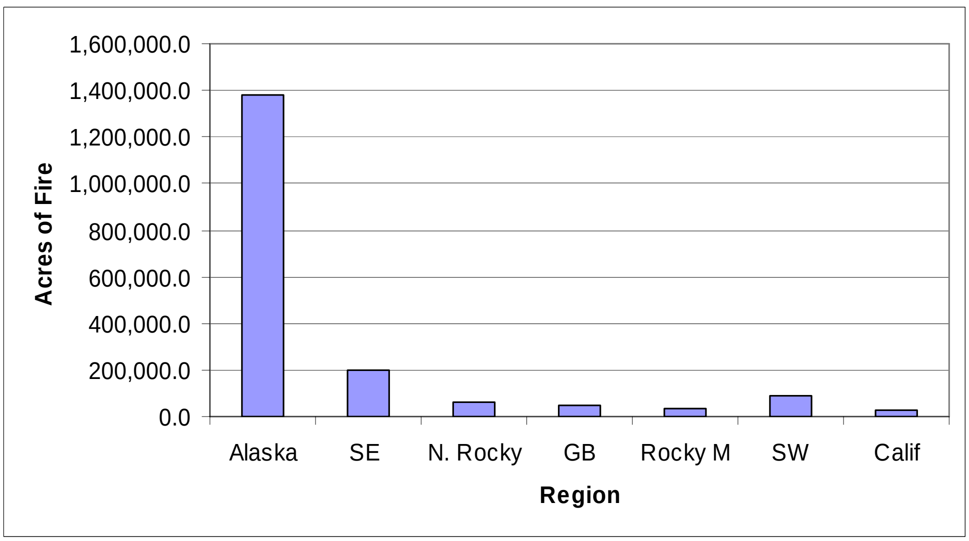
E: Number of fires by fire size category.



F: Number of fires by duration.



G: Acres of fire by region



The following table lists the number of records for each of the fire management and monitoring fire resource.

Fixed Wing

MTR-AF		AC_FW	Air Attk							
MTR	MGM	Lead	MTR	MGM	Air Tank 1	Air Tank 2	Air Tank 3	Air Tank 4	Seats	IR
143	33	6	8	11	7	2	0	0	9	4

Crews

Jmpr		IHC		20 Psn		10 Psn		7 Psn	
MTR	MGM	MTR	MGM	MTR	MGM	MTR	MGM	MTR	MGM
0	9	2	16	3	19	12	17	20	9

5 Psn		3 Psn		2 Psn		**H2O Tender**		
MTR	MGM	MTR	MGM	MTR	MGM	T1	T2	T3
18	13	15	6	56	22	5	8	1

Engines

E1		E2		E3		E4		E5	
MTR	MGM	MTR	MGM	MTR	MGM	MTR	MGM	MTR	MGM
0	0	0	2	0	5	7	14	0	4

E6	
MTR	MGM
31	29

Skigens	**Soft Tracks**	**Dirt Stuff**			**Excavator**
		Dozer1	Dozer 2	Dozer 3	
3	4	2	0	1	0

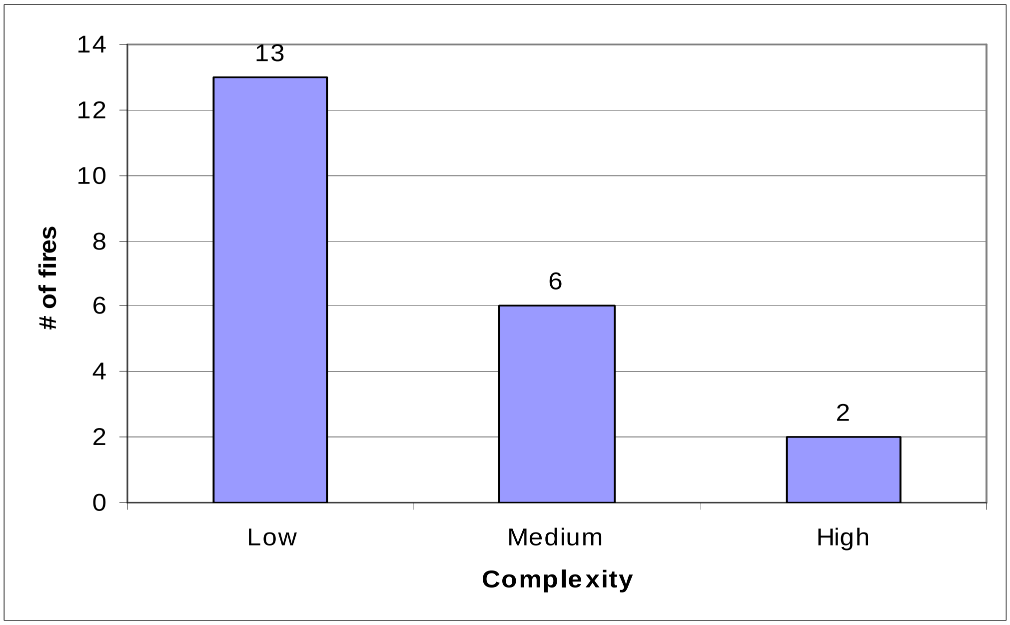
Tractor/Plow		
TP1	TP2	TP3
0	8	0

Motorgdr	RW1		RW2		RW3		**Stock Use**	**Boat**	
	MTR	MGM	MTR	MGM	MTR	MGM		MTR	MGM
6	1	2	6	15	80	57	4	1	1

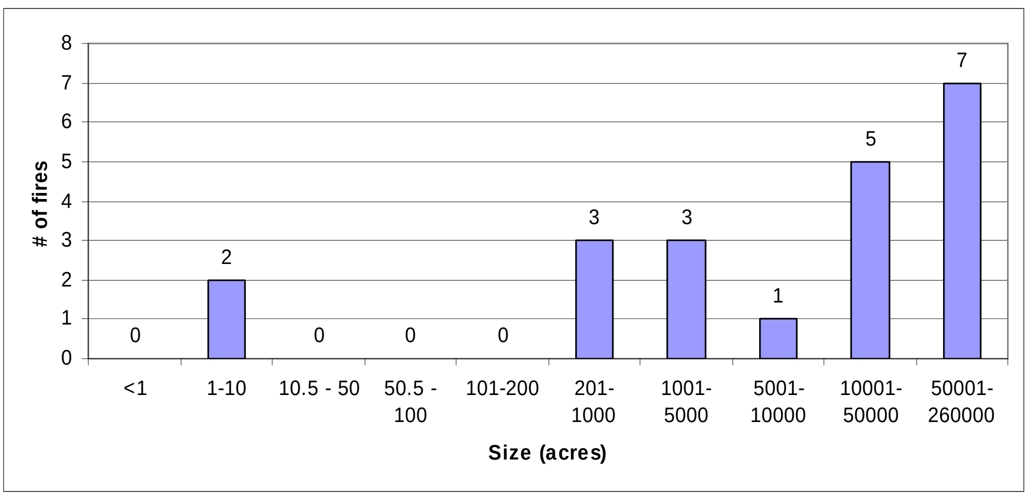
Summary by Region

Data Summary by Region: Alaska (AK)
There are a total of 21 fires in the data set from Alaska equaling 1,377,513 acres of fire.

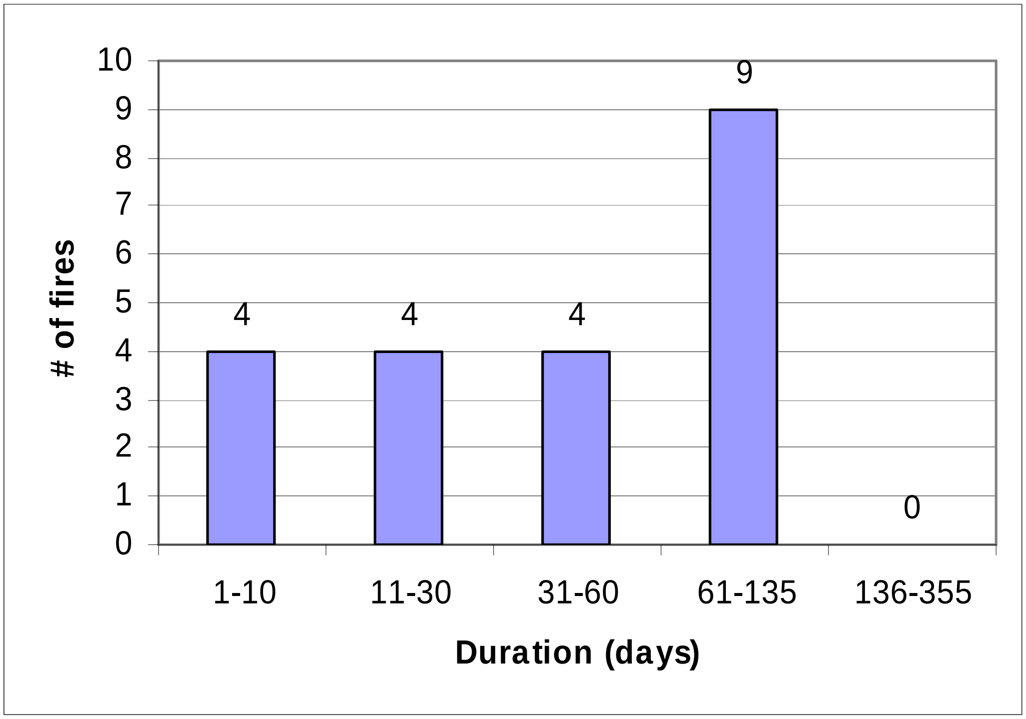
Alaska: number of fires by complexity.



Alaska: number of fires by fire size category.

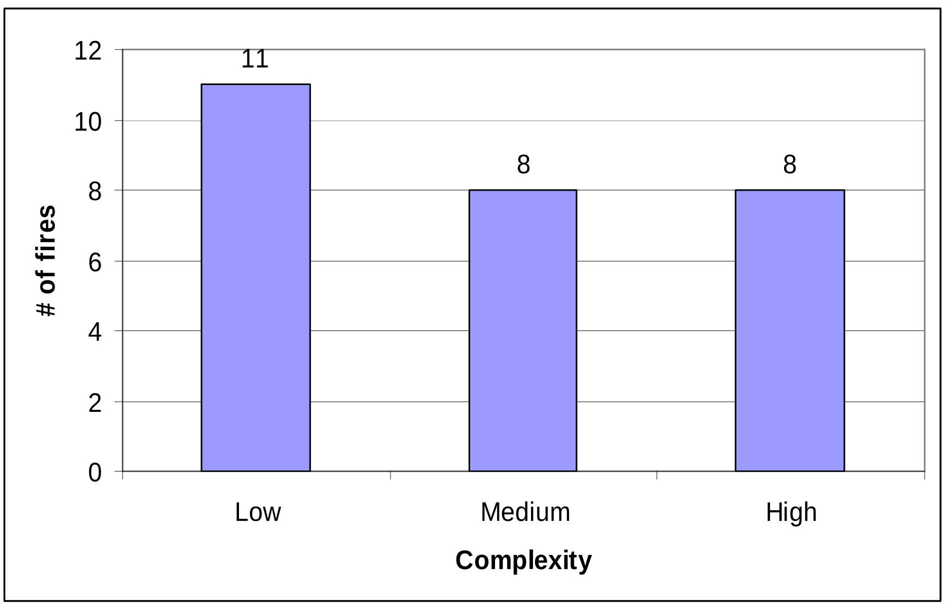


Alaska: number of fires by duration.

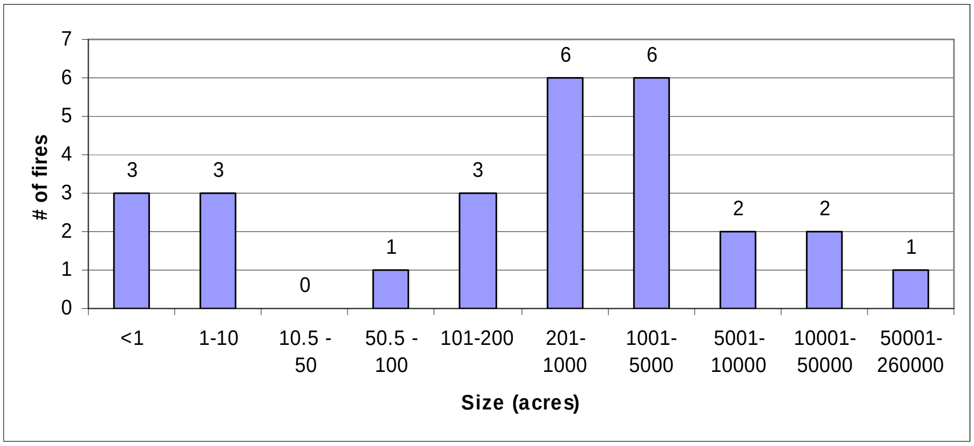


Data Summary by Region: Southern (SE)
There are a total of 27 fires in the data set from SE equaling 200,260 acres of fire.

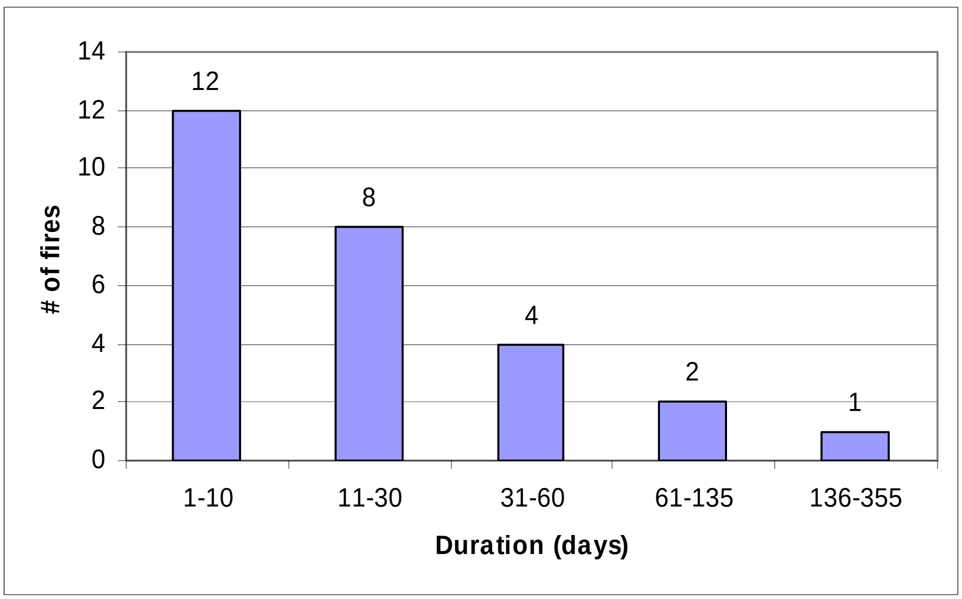
Southern: Number of fires by complexity.



Southern: number of fires by size category

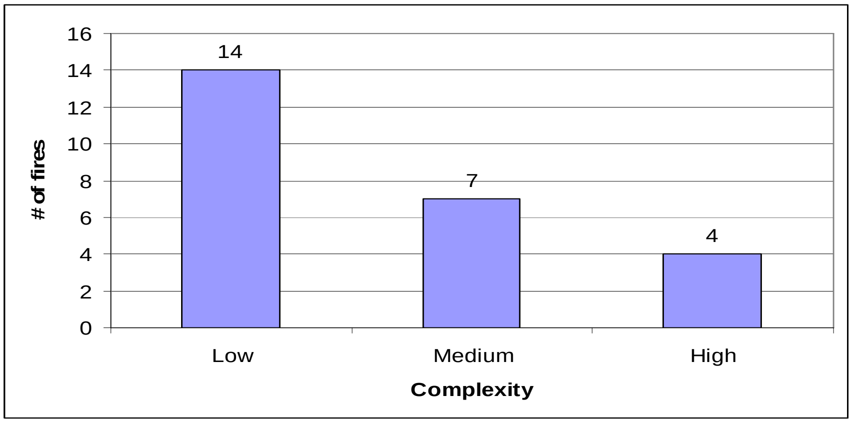


Southern: number of fires by duration.

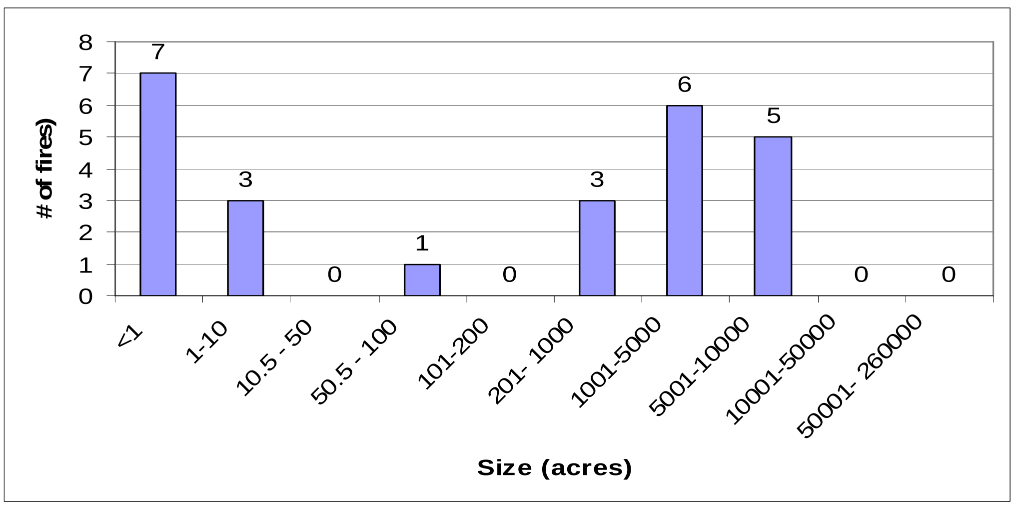


Data Summary by Region: Northern Rockies (NR)
There are a total of 25 fires in the data set from Northern Rockies equaling 61,946 acres of fire.

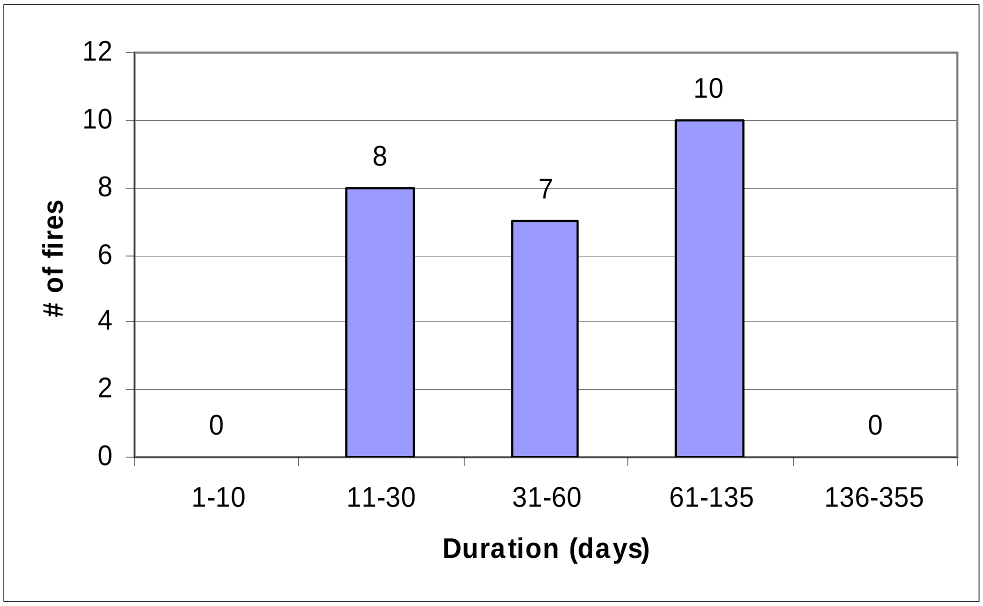
Northern Rockies: number of fires by complexity.



Northern Rockies: number of fires by size class.

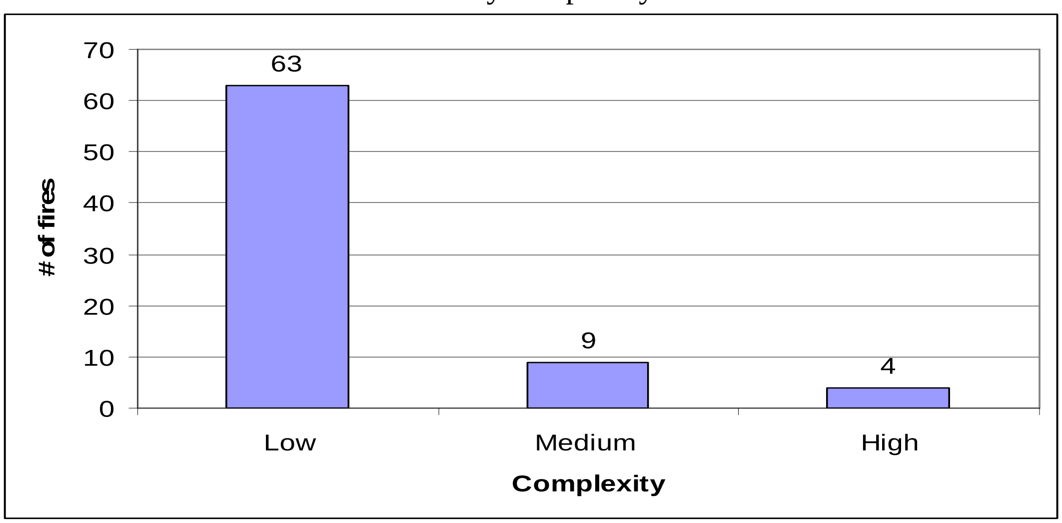


Northern Rockies: number of fires by duration.

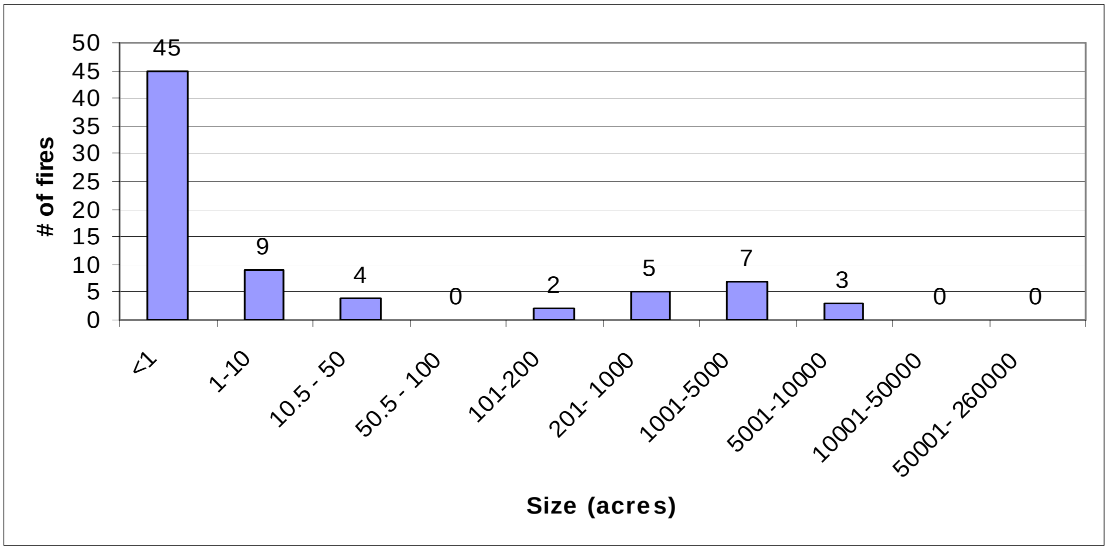


Regional Data Summary: Great Basin (GB)
There are a total of 75 fires in the data set from GB equaling 50,107 acres of fire.

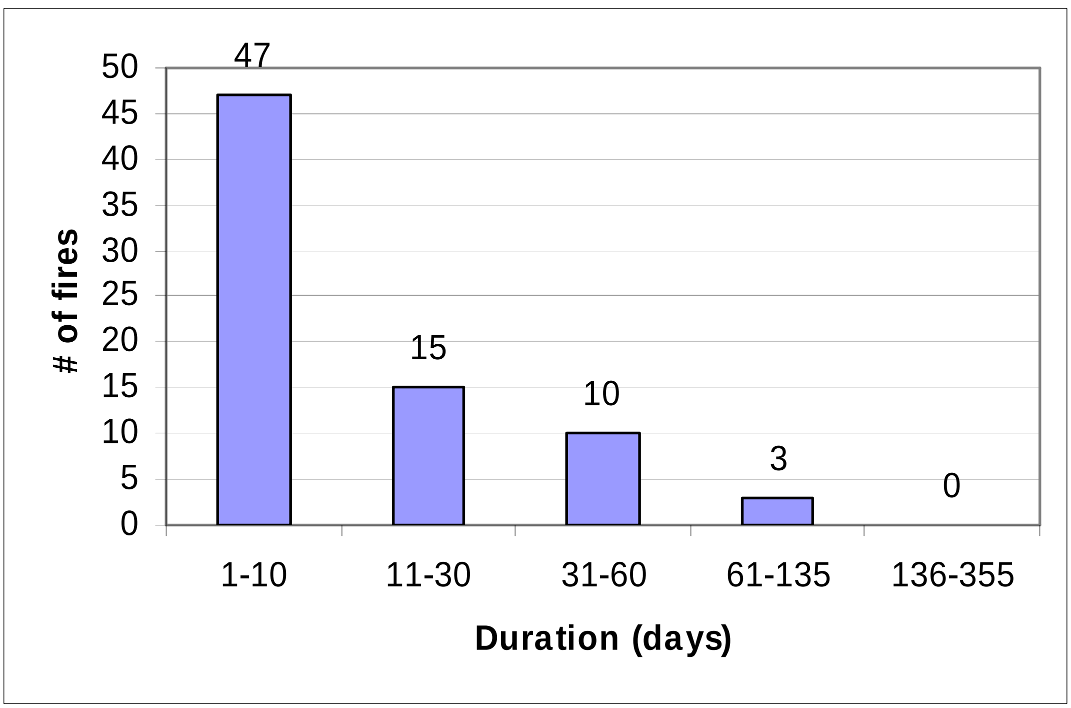
Great Basin: number of fires by complexity.



Great Basin: number of fires by size class.

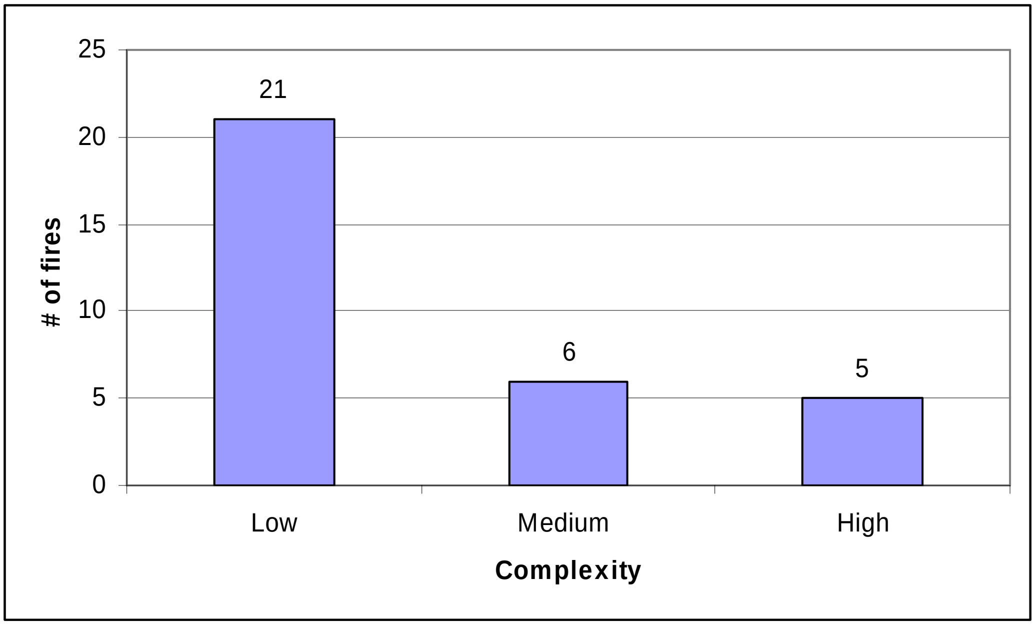


Great Basin: number of fires by duration.

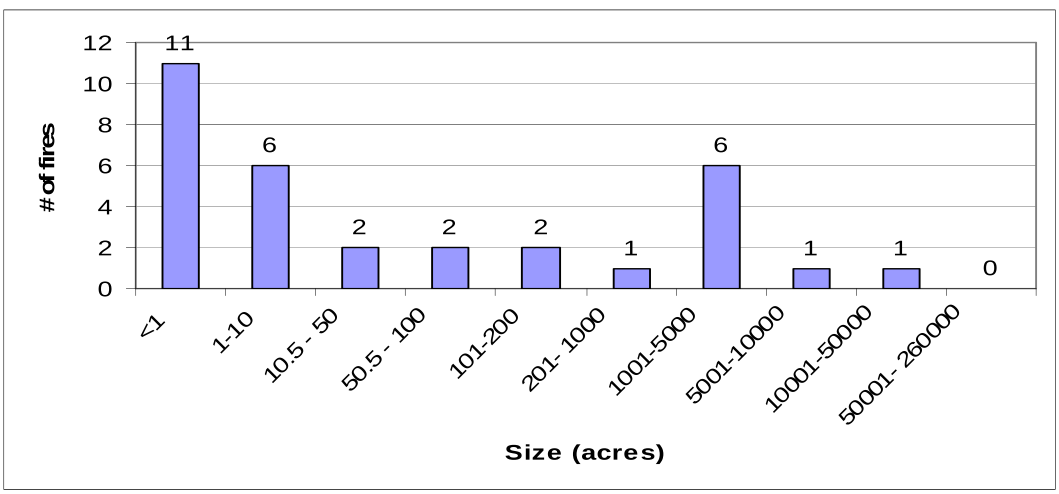


Regional Data Summary: Rocky Mountain (RM)
There are a total of 32 fires in the data set from Rocky M equaling 32,512 acres of fire.

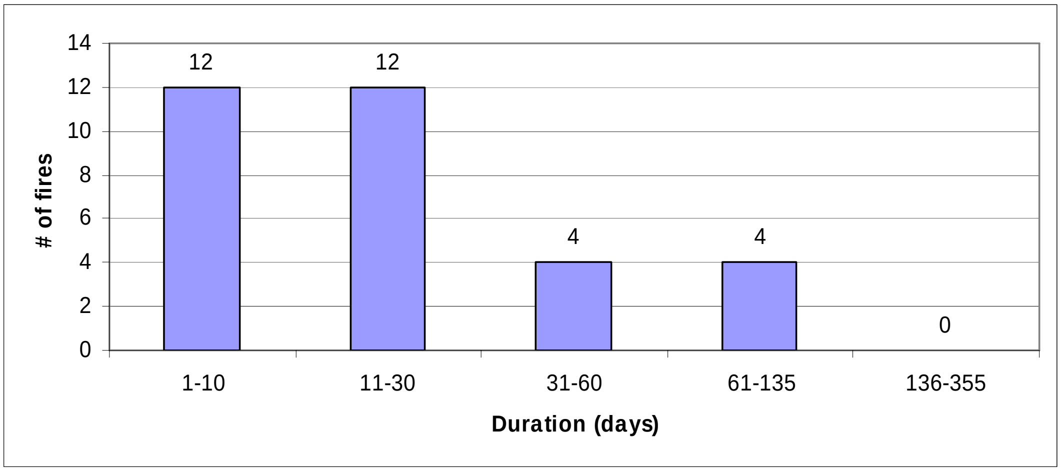
Rocky Mountain: number of fires by complexity.



Rocky Mountain: number of fires by size class.

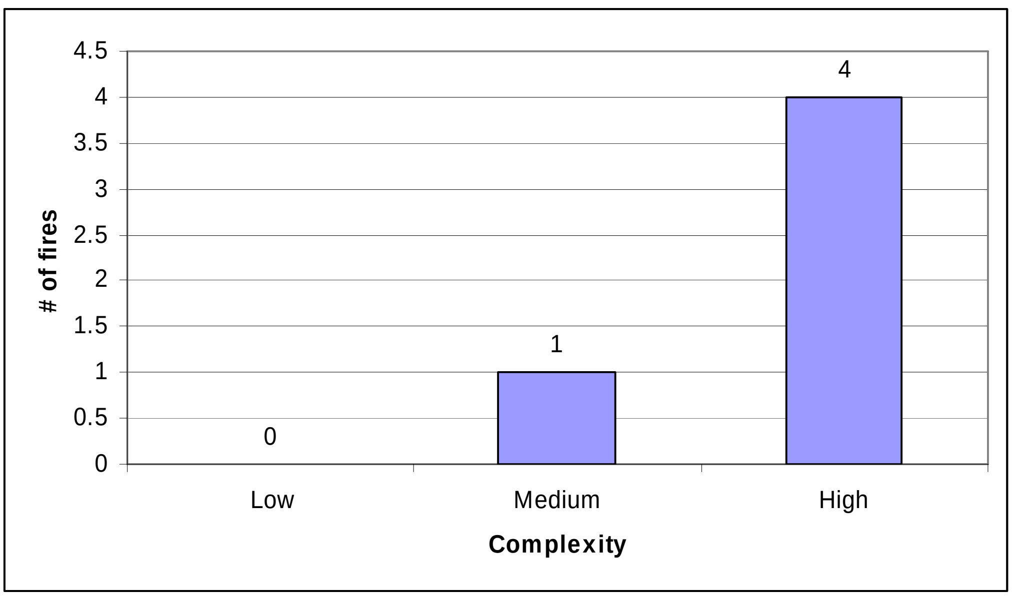


Rocky Mountain: number of fires by duration.

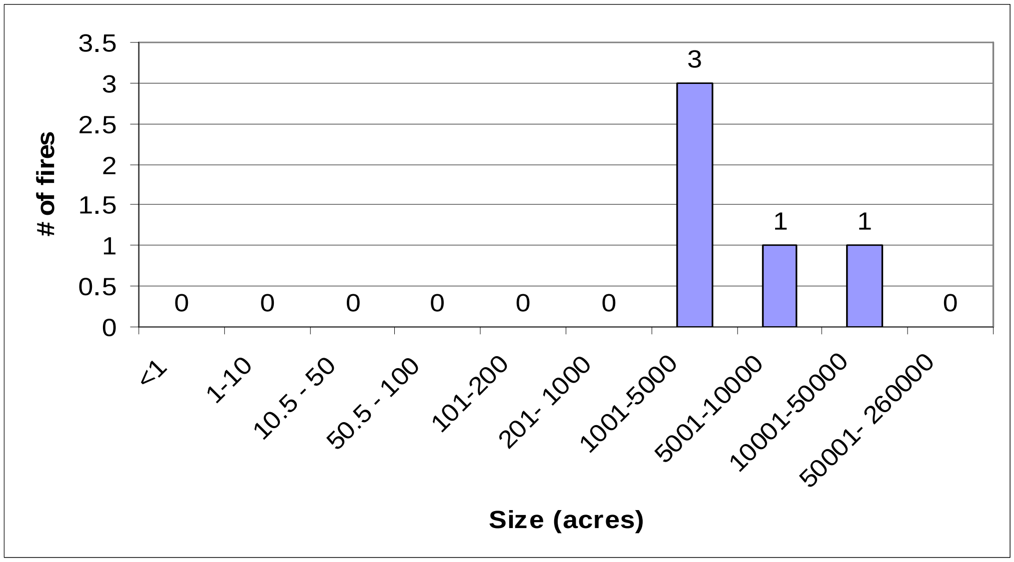


Regional Data Summary: Southwest (SW)
There are a total of 5 fires in the data set from SW equaling 90,300 acres of fire.

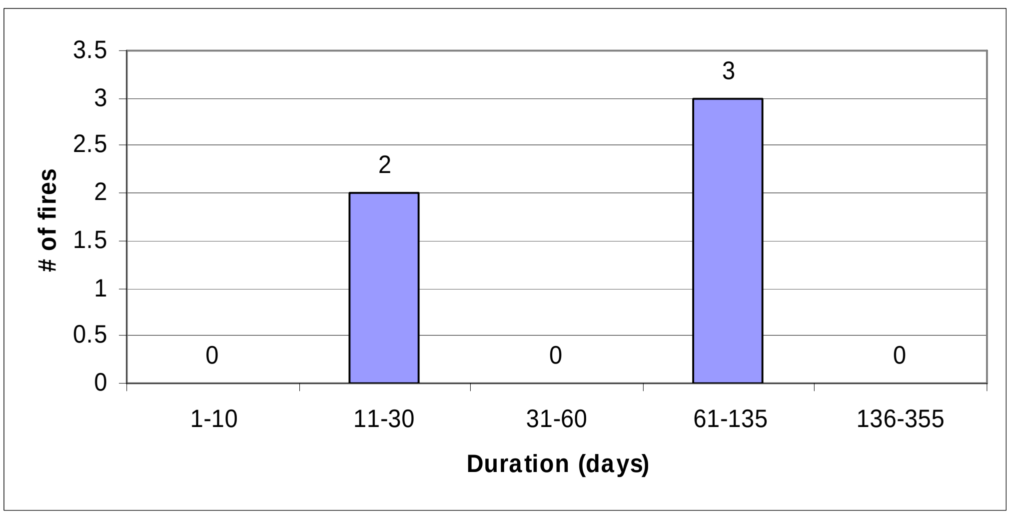
Southwest: number of fires by complexity.



Southwest: number of fires by size class.

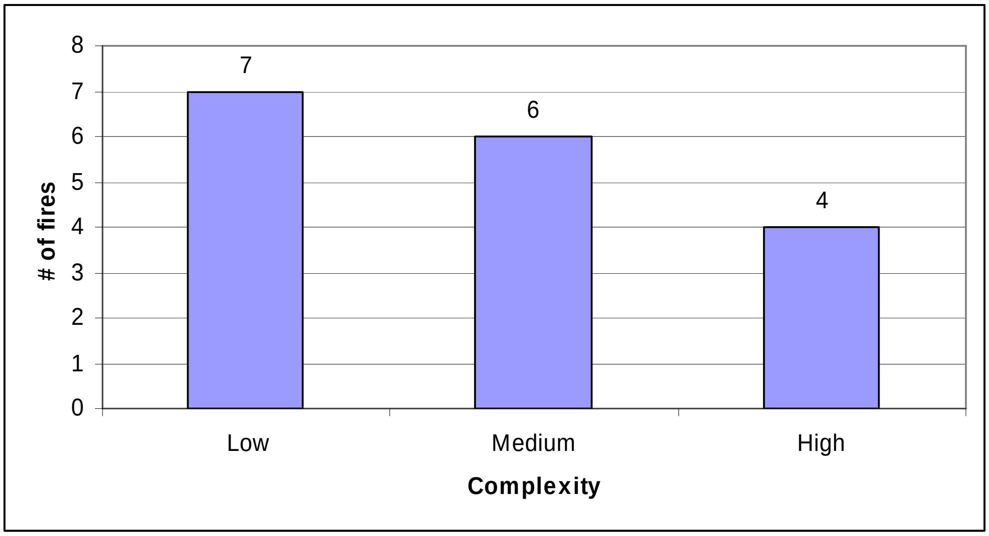


Southwest: number of fires by duration.

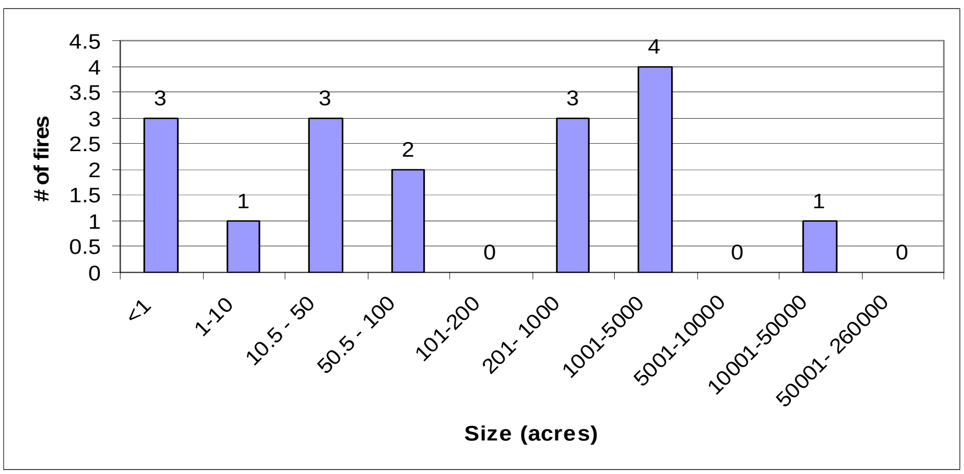


Regional Data Summary: California (CA)
There are a total of 17 fires in the data set from SW equaling 26,868 acres of fire.

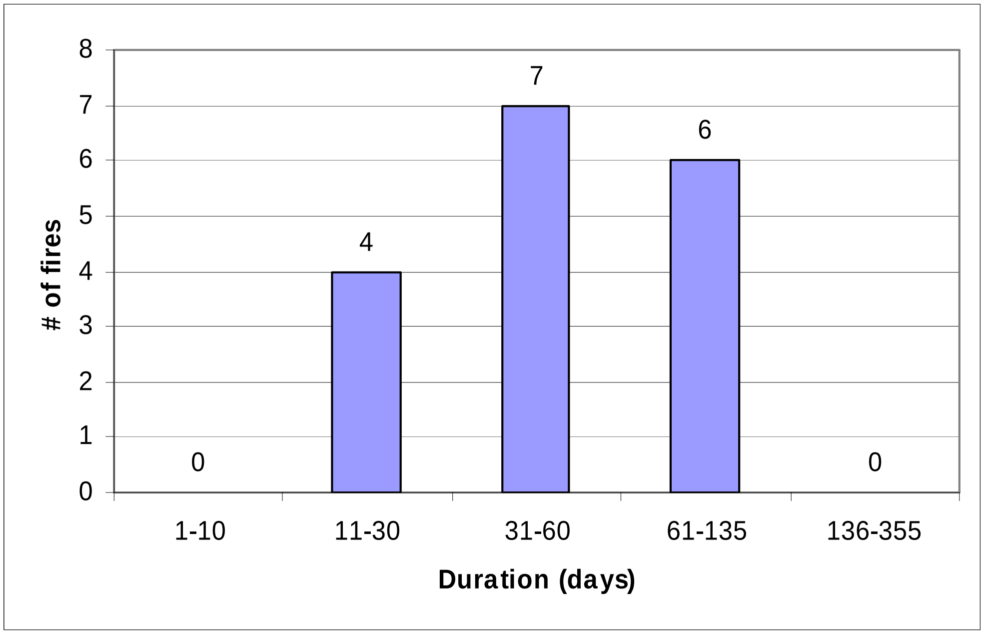
California: number of fires by complexity.



California: number of fires by size class.



California: number of fires by duration.



Outliers
Two records (fires) were identified as outliers and are listed in the table below and we removed these observations from the dataset.

				Mgt	Mtr			Complexity		
Name	No	ID	Yr	Score	Score	Size	Duration	High	Med	Low
BJBC	4722	GA-OKR	2002	3	5	124,110	354	1	0	0
Lodgepole	Lodgepole	ID-PAF	1999	7	6	3,853	58	0	0	1